2020 DOE Vehicle Technologies Office
Annual Merit Review

Computation of Metropolitan-Scale, Quasi-Dynamic Traffic Assignment Models Using High Performance Computing

Jane Macfarlane
Lawrence Berkeley National Laboratory
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Project ID: eems087

Overview

TIMELINE

- Start: September 2019
- End: October 2020
- 50 % complete

BUDGET

- Total project funding
- $250k / 1 year

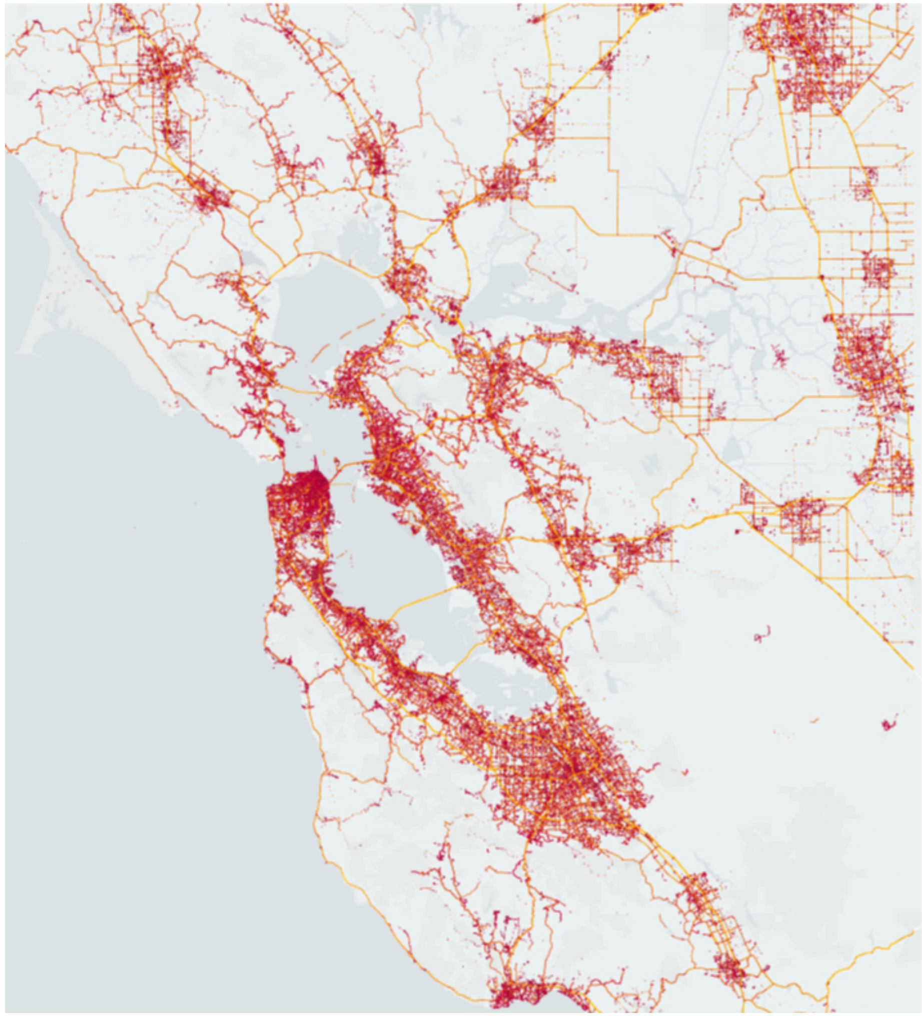
PARTNERS

- City of San Jose

BARRIERS

- Traffic assignment has traditionally focused only on user equilibrium travel time, not energy use at the system level. .
- Static traffic assignment is not realistic as it cannot capture time-dependent traffic demand and ensure the continuity of traffic flows.
- Traditional dynamic traffic assignment models have limitations in terms of scalability and computational efficiency.

Relevance and Project Objectives



Overall Goal:

- Use of high- performance computing to address the compute load of traffic assignment methodologies and optimize for energy use in large scale networks

Objective:

- Use of navigation apps: How to address problems created by full-information user equilibrium and system optimal cases?
- Distribute computational load of routing algorithm across multiple nodes
- Ensure the continuity of traffic flow and travel demand on each road link
- Improve the computational efficiency by coupling the Frank-Wolfe algorithms with the parallel discrete event simulator
- Incorporate multiple travel modalities into the optimization framework

Impact:

- Enable computationally-efficient solutions for large-scale transportation planning and operation decisions, considering better energy and time use

Approach

Develop a metropolitan-scale, quasi-dynamic, parallel traffic assignment model, leveraging static traffic assignment work developed in Phase I

Investigate time-based and energy-based optimization with a user focus, and a system level

Compare network metrics, energy, and mobility metrics for all four cases, i.e. user equilibrium time (UET) based, UE fuel based (UEF), system optimal time (SOT) based and SO fuel based dynamic traffic assignment

Aggregate demand for mode shift opportunities

- Build upon a preexisting architecture, Mobiliti. developed at LBNL for large-scale network simulation which allows sharing of maps and demand models across simulation and optimization algorithms.

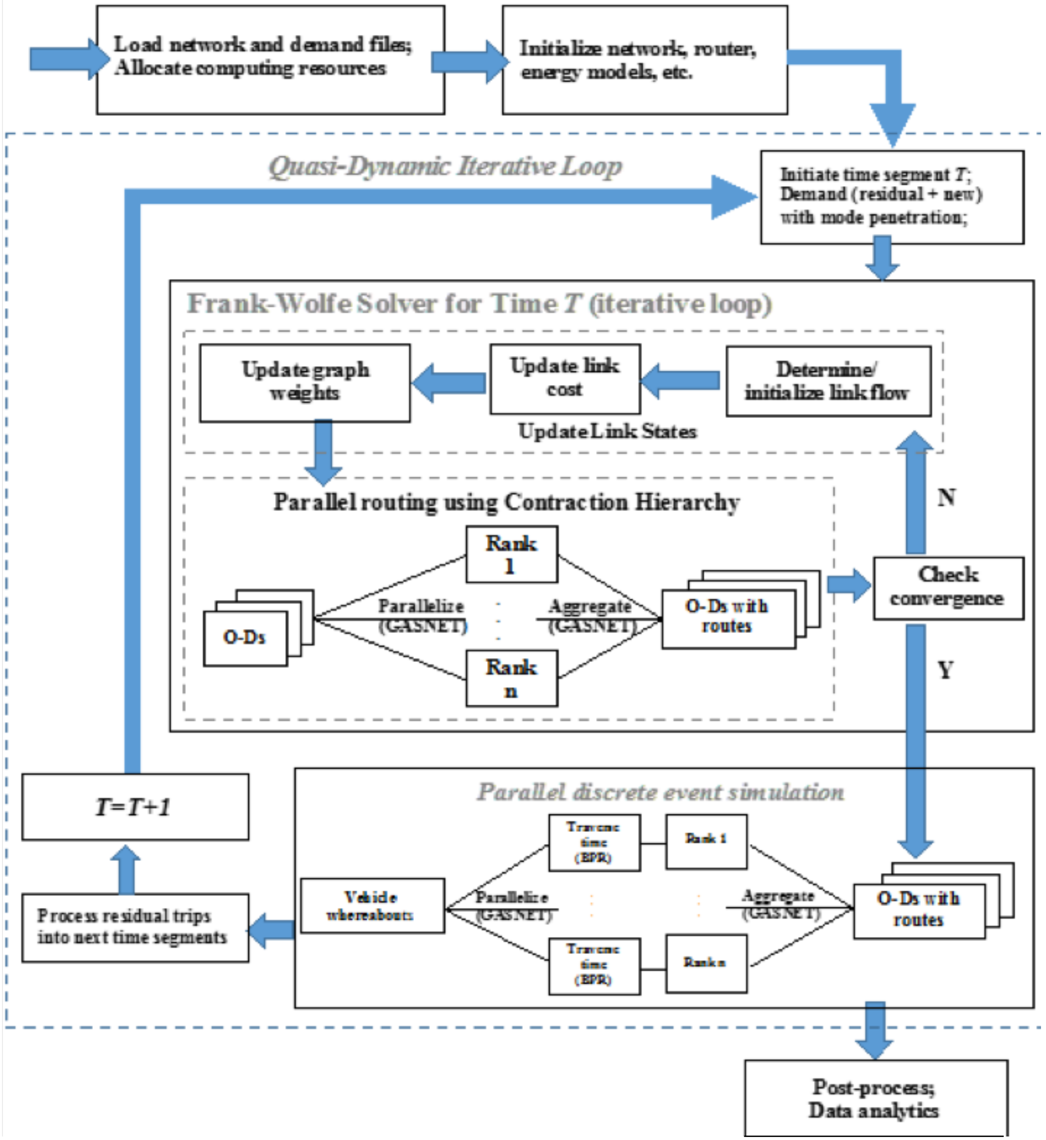
Computational Approach

Traffic Model
- Calibrated HERE map
- Validated travel demand model from SFCTA
- Import CSJ sensor data

Cost Function
- Travel Time
- Energy

Demand management
Parallel Solvers
- Frank-Wolfe
- Parallel discrete event simulation
- Update residual and new demands in each time segment

Quasi-Dynamic ETAP Approach Overview (using Cori)



Accomplishments : Using Data Driven Energy Models

Formulation of UE for Energy

Latency function for energy/fuel model based on BPR

$$t(Q_a) = t_a^0\left(1 + \alpha\cdot\left(\frac{Q_a}{c_a}\right)^\beta\right)$$

$$\mathrm{EF}_{\mathrm{fuel}}(v_a) = A + \frac{B}{v_a} + C\cdot v_a^2$$

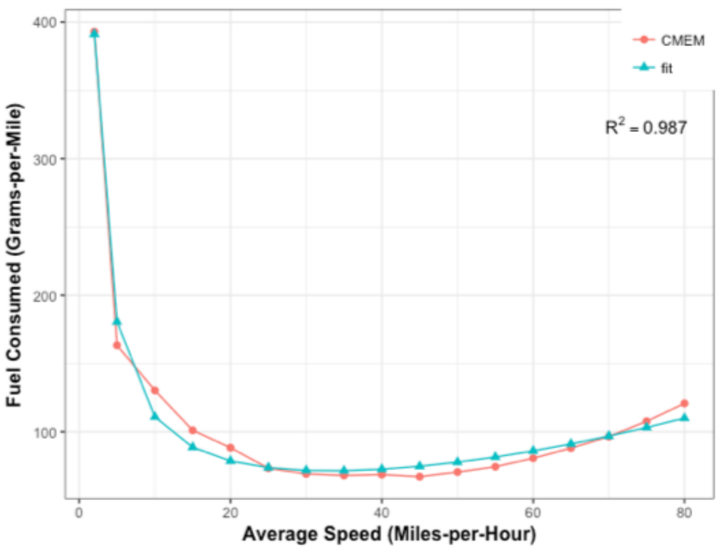
$$\mathcal{F}(Q_a) = Q_a\cdot L_a\cdot\left(A + \frac{C\cdot {v_a}^2}{\left(\alpha\cdot\left(\frac{Q_a}{c_a}\right)^\beta + 1\right)^2} + \frac{B\cdot\left(\alpha\cdot\left(\frac{Q_a}{c_a}\right)^\beta + 1\right)}{v_a}\right)$$

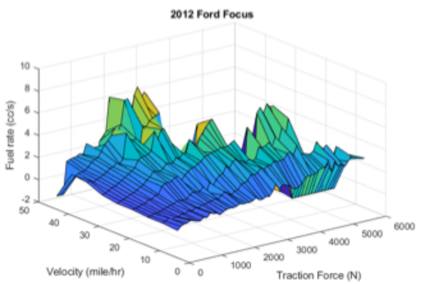
Q_a	flow on link a
c_a	capacity of link a
L_a	length of link a
t_a^0	free flow travel time of link a
v_a	free flow speed of link a

$$v_a = \frac{L_a}{t_a^0}$$

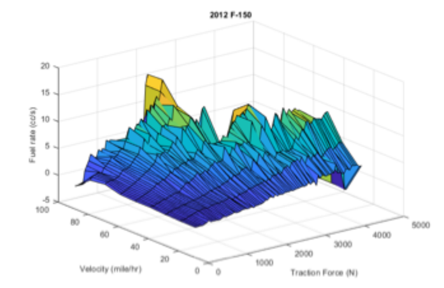
$$\alpha = 0.15$$

$$\beta = 4$$

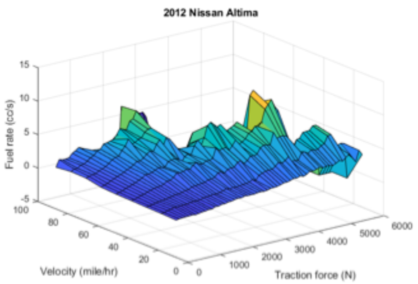




Compact Vehicle



Mid Size Vehicle



MD Truck

QDTA in San Jose

Number of links: 75,161

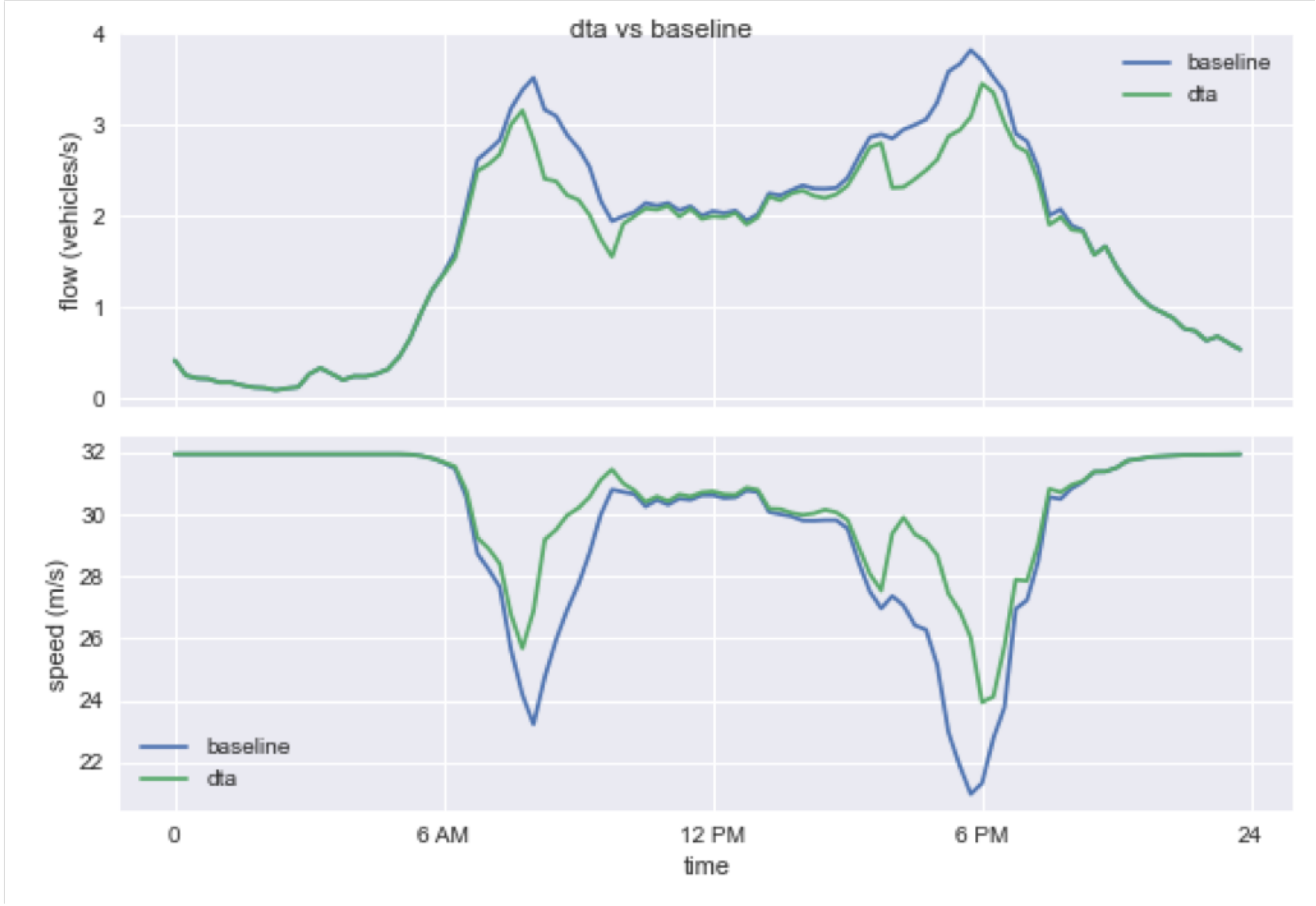
baseline

dta-uet

QDTA in SF Bay Area

Number of links: 1,008,959,
Number of trips: 14,256,867,
Solved in less than 10 mins with a 2-hour time interval

Optimized Flow and Speed

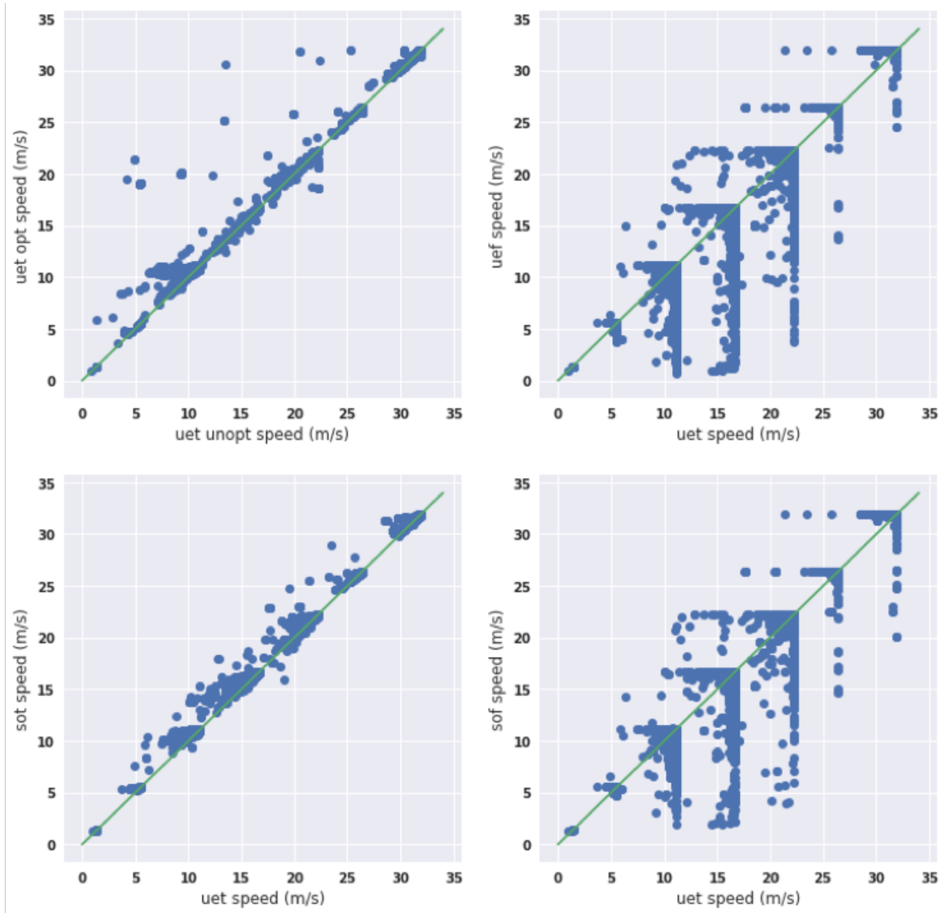


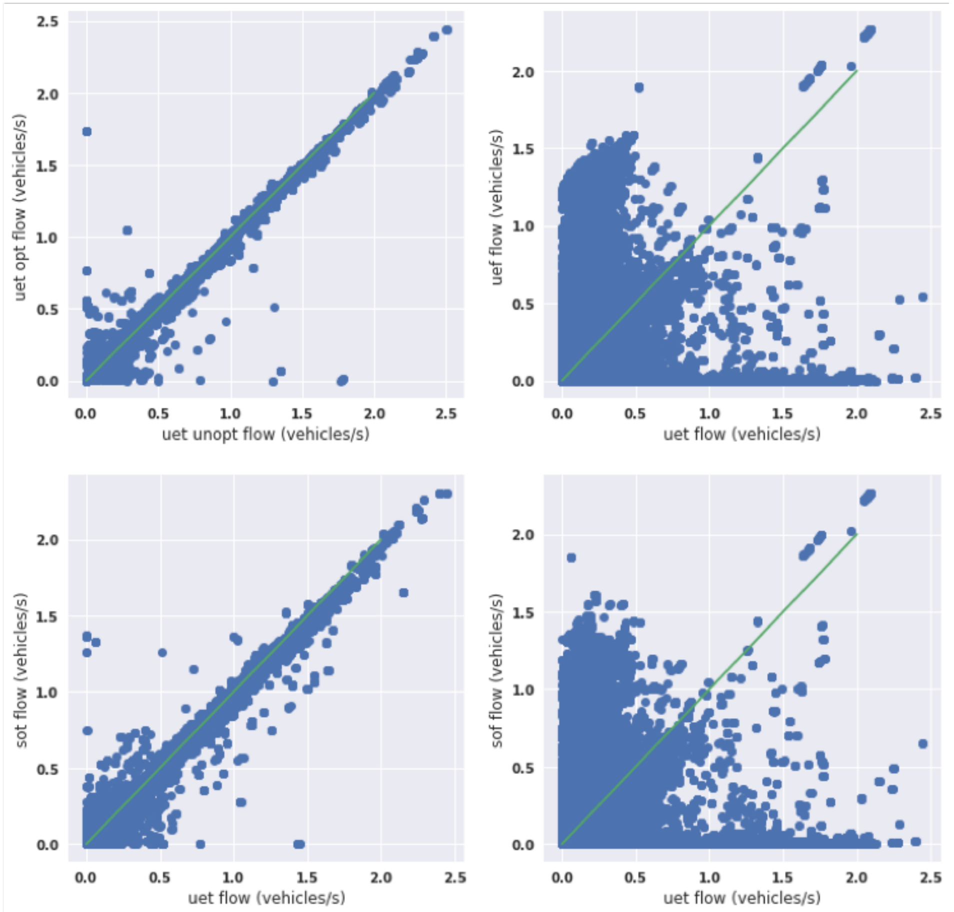
Link_ID : 820741359

Flow and speed profiles are improved by Quasi - DTA

Time & Energy QDTA Optimization

UET Unopt : Baseline Shortest Travel Time
UET: User Equilibrium Travel Time Optimized
UEF: User Equilibrium Fuel
SOT: System Optimal Travel Time Optimized
SOF: System Optimal Fuel





- Energy-based optimization reduces link speeds to optimal speed range (more sensitive to speeds)
- QDTA changes the flow distribution over links

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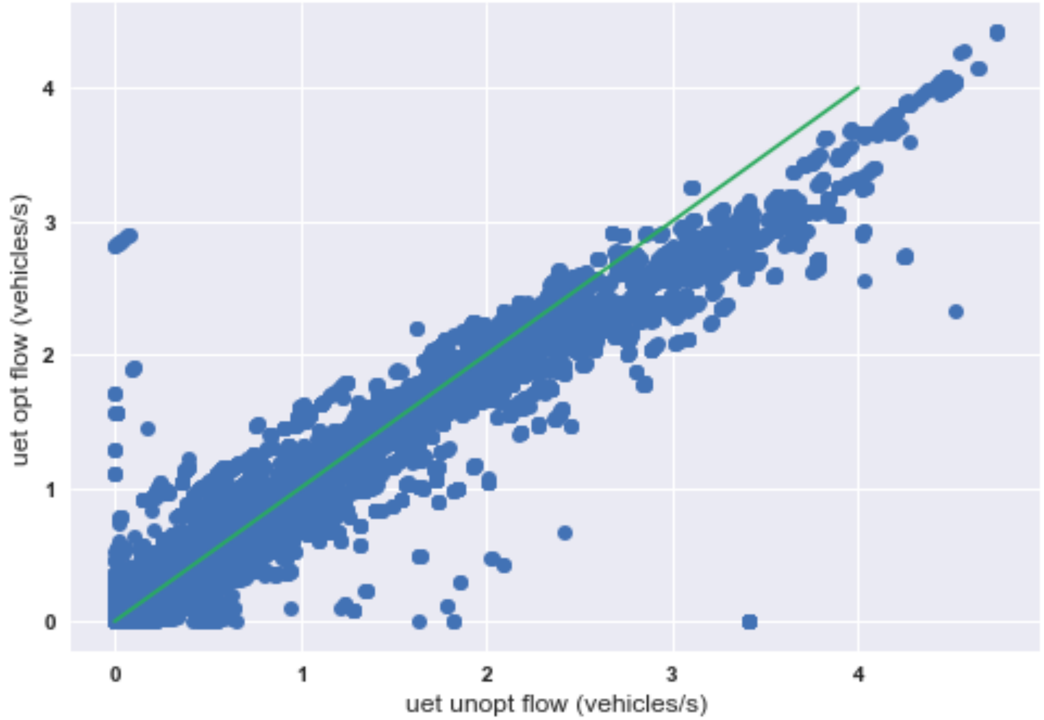
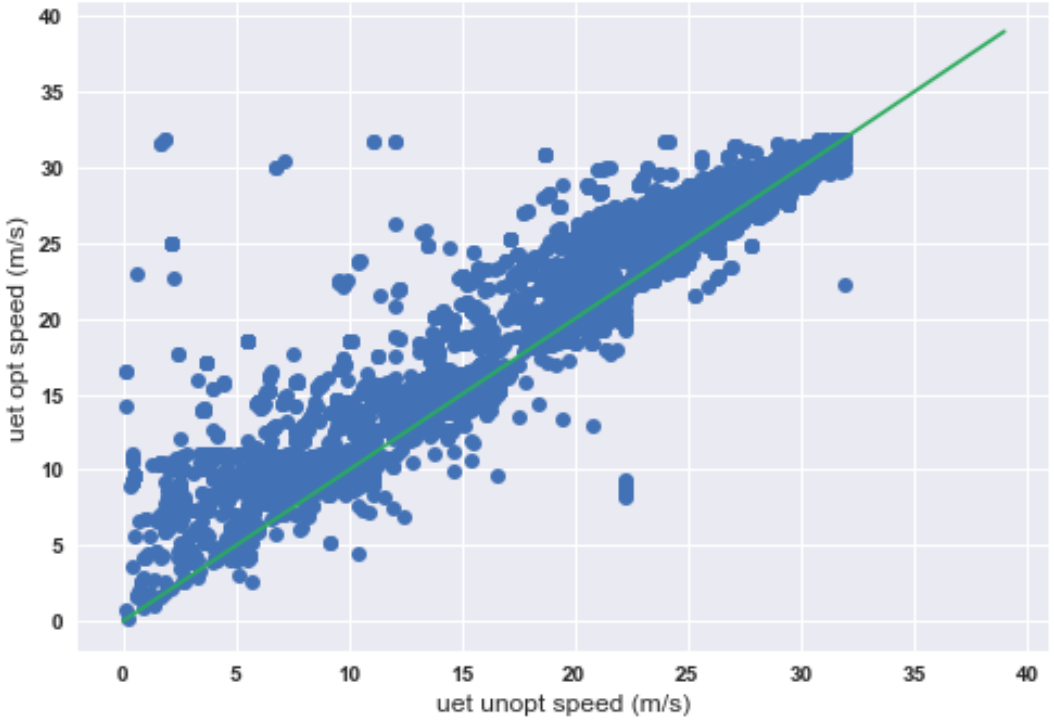
Time & Energy QDTA Optimization

Better time resolution of Quasi-DTA (Shorter time interval) improves the traffic optimization performance in terms of traffic flows and speed profiles.

Time Interval: 1 Hour



Reduced traffic volumes on more road links compared with the previous case study (time interval =2 hour)



Improved the speed profiles over more road links

Collaboration and Coordination

Challenges and Proposed Future Research

- Collaborate with the City of San Jose
  - Incorporate the city sensor data into Quasi-DTA framework
  - Validate the optimization models

- Improve convergence behaviors of the QDTA algorithms
  - Adaptive step size selection algorithms to endure the convergence, especially in time steps with high travel demand
  - Improve the fuel-based optimization associated with non-convex relationship
  - Further reduce the time interval from 2 hour to 15 mins and 5 mins

- Further develop AI/deep learning solutions to the traffic management
  - Use QDTA as a fast solver to provide ensembles of training samples into machine learning/ AI framework

Any proposed future work is subject to change based on funding levels.

Summary

- Traffic optimization using Quasi-Dynamic approaches significantly reduced traffic congestion and fuel consumption. Fuel-based optimization is very sensitive to speed profiles and time-based optimization is sensitive to time-window size within the Quasi-DTA.
- This implementation of Quasi-DTA is computationally efficient, leverages supercomputers and parallel discrete event simulation.
- Provide a framework to incorporate multiple travel modalities into the QDTA framework and use QDTA as fast solvers to accelerate the development of AI/machine learning based traffic management approaches.